SETAC PRESS
Environmental Toxicology and Chemistry, Vol. 21, No. 3, pp. 672–681, 2002
Printed in the USA
0730-7268/02 $9.00 + .00

EVALUATION OF THE AgDISP AERIAL SPRAY ALGORITHMS IN THE AgDRIFT MODEL

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(*Received* 26 *September* 2000; *Accepted* 13 *August* 2001)

Abstract—A systematic evaluation of the AgDISP algorithms, which simulate off-site drift and deposition of aerially applied pesticides, contained in the AgDRIFT® model was performed by comparing model simulations to field-trial data collected by the Spray Drift Task Force. Field-trial data used for model evaluation included 161 separate trials of typical agriculture aerial applications under a wide range of application and meteorological conditions. Input for model simulations included information on the aircraft and spray equipment, spray material, meteorology, and site geometry. The model input datasets were generated independently of the field deposition results, i.e., model inputs were in no way altered or selected to improve the fit of model output to field results. AgDRIFT shows a response similar to that of the field observations for many application variables (e.g., droplet size, application height, wind speed). However, AgDRIFT is sensitive to evaporative effects, and modeled deposition in the far-field responds to wet bulb depression whereas the field observations did not. The model tended to overpredict deposition rates relative to the field data for far-field distances, particularly under evaporative conditions. AgDRIFT was in good agreement with field results for estimating near-field buffer zones needed to manage human, crop, livestock, and ecological exposure.

Keywords—Spray drift Pesticides Modeling

BACKGROUND AND OBJECTIVES

Drift of air-borne pesticides beyond the target site during aerial applications is a source of environmental concern due to the potential for human health impacts, downwind contamination and damage to crops and livestock, and endangerment of ecological resources. The Spray Drift Task Force (SDTF), a consortium of pesticide registrants, has gathered field and laboratory data [1] based on the assumption that pesticide drift is primarily a function of application techniques (e.g., droplet size and release height), environmental conditions, and physical properties of the spray solution and not of the active ingredient per se. The sensitivity of drift to numerous factors, including atmospheric conditions [2–6] and application equipment [6–8] and the inherent variability of field-trial results [8], makes field testing the full range of possible meteorological and application scenarios difficult. Modeling provides a coherent framework for evaluating the potential risks of spray operations and the potential effectiveness of mitigation options. Both the SDTF and the U.S. Environmental Protection Agency, Office of Pesticide Programs (OPP), support the use of a spray drift modeling tool incorporating input databases and postprocessing utilities to improve the efficiency, cost effectiveness, and reliability of the product evaluation and registration process. The AgDRIFT® model, which was developed to fill this need, is described in detail in a companion article [9]. Since substantial productivity costs to applicators and growers and potential damage to the environment hinge on the result of regulatory decision-making, models used in this process must have demonstrated scientific credibility (i.e., model algorithms must be based on sound science with demonstrated model performance). AgDRIFT contains empirical curves to estimate drift from ground and orchard airblast applications and AGricultural DISPersal (AGDISP) [10] mechanistic algorithms to estimate drift from aerial applications. The primary purpose of the current article is to provide a systematic evaluation of the aerial drift algorithms incorporated into AgDRIFT to support its use in a regulatory setting.

An extensive body of literature has developed with respect to establishing the scientific soundness of models for use in environmental assessments. Beck et al. [11] identified two features that are intuitively used to judge a model: the composition of the model and the performance of the model. Compositional validity is based on the intrinsic structure of the model and some consensus judgment about the constituent hypotheses represented in the model. Judgment of composition reflects the generic properties of the model irrespective of the current task. Model performance is evaluated based on the suitability of a model for undertaking a specific task. An important part of measuring performance is determining the magnitude of the risk of making a wrong decision stemming from applying the model to the task at hand. The exposure estimates generated by AgDRIFT are used to make decisions regarding allowable pesticide use. If these decisions do not sufficiently restrict pesticide use, serious environmental consequences occur, whereas overly restrictive decisions can have significant economic repercussions. The magnitude of the decision-making

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Paper NERL-ATH-ERD-00-043, U.S. Environmental Protection Agency. This article has been reviewed in accordance with the U.S. Environmental Protection Agency's peer and administrative review policies and has been approved for publication. Mention of trade names or commercial products does not constitute endorsement or recommendation for use by the U.S. Environmental Protection Agency, the authors, their employers, or the Spray Drift Task Force.

risk, however, is dependent on the specific product and product use. Thus, even for a relatively well-defined model application, the absolute performance requirements are dependent on the uncertainty level acceptable in the individual case.

Agricultural dispersion, a well-documented Lagrangian-type model [10] still under active development, serves as the computational engine for AgDRIFT. The selection of AGDISP as the computational engine for AgDRIFT was based on its widespread scientific acceptance (i.e., compositional validity) and the appropriateness of the structure of the model for the problem of estimating aerial spray drift. The AGDISP has an extensive history of use and development by several federal agencies, including the National Aeronautics and Space Administration (NASA), U.S. Department of Agriculture Forest Service, and the U.S. Army. In addition to the mechanistic aerial application algorithms, AgDRIFT contains empirical curves to estimate drift from ground and orchard airblast application of pesticides. It consists of a Visual Basic Windows® (Microsoft, Redmond, WA, USA) interface, access to input data libraries, a toolbox for analysis of output, and plotting and export utilities. AGDISP, a FORTRAN model, is compiled as a digitally linked library incorporated into the visual shell. Teske et al. [9] describe in detail the structure of AgDRIFT, the incorporation of AGDISP into this framework, the scientific basis for the algorithms, and recent improvements in the computational algorithms.

A number of studies have examined the performance of AGDISP (or AGDISP as the near-wake component in Forest Service Cramer–Barry–Grim [FSCBG] [12]) with field observations. A sensitivity analysis and evaluation study of AGDISP 6.1 and two other spray drift models were performed for Environment Canada [13]. For a series of 18 experimental treatments, observed results differed from the three model estimates by a factor of two or less. The outputs against which the models were compared included maximum deposition, location of maximum deposit, integrated deposit, and the median integrated deposit location. Several field studies were performed by the Forest Service over forested areas, and the results were compared with FSCBG [12], which also utilizes AGDISP as the near-field model. These studies involved relatively high flight (10–60 m) releases. The model to field-data comparisons were primarily graphical, showing good comparisons with calculated values for R^2 between predictions and observations generally >0.5. The New Zealand Forest Research Institute, Rotorua, New Zealand [14], compared the FSCBG/AGDISP combination with field results of 12 separate applications over grasslands with 3 separate nozzle types and a 10.3-m release height. These researchers concluded that the modeling system was useful in assessment of the effectiveness of spray equipment and for defining operational and meteorological variables that will minimize drift. Anderson et al. [15] compared the FSCBG/AGDISP combination to results from 17 releases over fully leafed 16-m mixed oak forest. These researchers found the model acceptable in predicting average (over several trials) deposition but noted that the model results as expected did not reflect the high run-to-run variability observed in the field data.

The major focus of this study is to provide a performance evaluation of AgDRIFT, i.e., an evaluation of the model specifically in the context of agricultural pesticide product registration. Previous evaluation efforts on the computational engine of AgDRIFT (AGDISP) have focused on the use of the technology in high-flight (>10 m) forestry applications. Pesticide registration use will more frequently be for low-flight row crop application. The primary proposed use for AgDRIFT in regulation and safety studies is to evaluate exposure from deposition of pesticides onto aquatic and terrestrial systems near the application area. Primarily, the model use will be limited to within 300 m (~1,000 ft) of the edge of the field. The deposition values generated by AgDRIFT will be used in the regulatory context to determine the size of buffer zones in combination with other label restrictions needed to reach a safe level of exposure. The evaluation efforts thus focus on model performance in predicting deposition within 300 m of the application zone for relatively low-flight applications.

The information on the model performance will be presented in the form of graphical analyses and summary statistics. There are three general questions that these analyses are intended to address: How well does the model predict the field-trial results on average? To what extent do the model predictions vary from the measured results? Can the quality of the fit between the model and the field data be related to specific application variables or environmental factors? The specific goal of the buffer zone analysis is to evaluate the potential differences in buffer zone size developed from model simulations versus those from field-trial observations and to infer the general magnitude of risk associated with these important regulatory estimates.

A number of model developers have proposed a variety of metrics and statistical test methodologies for model evaluation [16–19]. Reckhow et al. [16] recommend that evaluations include a combination of graphical comparisons and statistical tests appropriate to the context of the proposed use. The approach in this article is to present a variety of measures of model performance to allow the user to evaluate acceptability of model performance for various perspectives; i.e., we are attempting to supply the reader and model user with sufficient information to perform their own hypothesis testing and to understand the behavior and limitations of the model. Analysis is presented both graphically (quantile-quantile [Q-Q] plots and box-and-whisker plots) and as summary statistics (e.g., mean and standard deviation of model-observation differences at various downwind distances). Our analysis evaluates performance at individual downwind distance locations separately since the rapid decline in deposition with increasing downwind distance can mask the response to other variables. In addition to performance categorized by downwind distance, model performance is also examined as a function of major application variables and meteorological conditions.

MATERIALS AND METHODS

Field-trial data

A total of 180 aerial trials were conducted by the SDTF during a series of three distinct sets of field studies. Details of these studies are provided in Hewitt et al. [1]. The studies were conducted in pairs with each pair consisting of a standard treatment and a variable treatment. The application variables were held constant for all standard treatments and systematically altered during the study for the variable treatments. Four flight lines were applied for most of the trials, with each having a 13.7-m swath width. Deposition samples were taken on horizontal alpha-cellulose cards along the four parallel flight paths and along three parallel lines perpendicular to the flight path. In many cases, the three line replicate cards were composited

Table 1. Summary of field-trial conditions

Meteorological conditions	Mean	Minimum	Maximum
Wind speed (m/s) at 2-m height	4.4	1.3	7.7
Relative humidity (%)	57	7	93
Temperature (°C)	25	0	35
Atmospheric stability	Neutral to unstable		

Application parameters	Standard	Variable
Drop size (VMD) (μm)	238	160–811
Flight height (m)	2.5 ± 0.5	1.6–9.3
Carrier	Water	Water, oil
Tracer	Diazinon	Malathion, carbaryl, orthene
Aircraft	AgHusky	AgHusky, AirTractor AT-502, WASP
Target vegetation	Uniform short grass	Uniform short grass, cotton canopy

prior to analysis to reduce analysis costs. Downwind deposition values used in the analysis were either the composite value or the average value of the three line replicates at a given downwind distance when analyzed separately. All data were collected using the U.S. Environmental Protection Agency mandated Good Laboratory Practice Standards (GLPS). The greatest uncertainty in the data is at low-deposition, far-field collection stations (≥305 m beyond the downwind edge of the field), where collection efficiency and sample recovery become potential data-quality issues [1]. Data beyond the 305-m collector station were not used in the analyses presented here. The range of meteorological conditions and application variables during the field trials is summarized in Table 1.

For this analysis, 19 of the 180 treatments were removed from the dataset for the following reasons. Two of the variable treatments used a spray tank mix containing two tracers (malathion and carbaryl). Since these two tracers did not stem from independent treatments, only the malathion results were used in the analysis. The carbaryl and malathion measured results agreed well in both of the dual tracer treatments (with an average difference of 15%). Two treatments were eliminated due to their nonstandard downwind distance coordinate system. These treatments were applied deep inside a cotton field to examine canopy effects. Four single-swath and two full-field (20-swath) treatments were removed to make the remaining treatments (all with 4 swaths) easier to compare. The number of swaths of spray applied is a significant factor in the total mass deposited; keeping these treatments in the dataset would have increased the complexity of the analysis and masked more subtle effects. Thirteen treatments were eliminated when the wind angle deviated substantially (i.e., mean wind angle plus a standard deviation was greater than 45°) from the card line during the course of the experiment and an analysis of the field geometry indicated that a substantial amount of material missed the downwind collectors. The results presented here are based on the remaining 161 treatments.

Model simulations

AgDRIFT inputs drive the various elements of the model used to approximate the physics within the wake behind the spray aircraft and subsequent drift through the ambient atmosphere [9,10]. These inputs were either measured during the field trials, measured in the laboratory or wind tunnel, or estimated from published literature. No input values were obtained by calibrating to the field deposition results. The complete list of AgDRIFT input requirements is detailed in [9]. These inputs describe the aircraft and its power plant (propeller); the nozzle number, location, and the droplet size distribution they create; the spray material physical properties; ambient meteorology; and field and spray geometry.

Aircraft and engine characteristics required as model inputs include the planform area, fixed-wing semispan or helicopter rotor radius, flight spraying speed, aircraft weight, propeller blade radius, propeller or helicopter rotor RPM, spatial location of the blade hub relative to the tip of the trailing edge of the wing, engine efficiency, and aircraft drag coefficient. Specific characteristics of the three SDTF field-test aircraft—Cessna AgHusky 188, Air Tractor AT-502, and Aerodyne Wasp—were obtained from aircraft compendia [20,21] and from telephone conversations with engineers at the three manufacturing facilities. Actual spraying speeds for each of the field trials were recorded in the field as described in [1]. Bilanin et al. [10] suggest that the aircraft drag coefficient be set to 0.1 and the engine efficiency be taken as 0.8, values that were retained in these simulations.

Nozzle placement information required as input includes the spatial location of the spray boom relative to the centerline of the aircraft, the vertical distance to the tip of the trailing edge of the wing (or the rotor plane of the helicopter), and the number and spacing of nozzles on the spray boom. Specific details of the boom setup for the three SDTF field-test aircraft were recorded during the field trials.

The droplet size distributions for the nozzles and test substances sprayed in the SDTF field trials were obtained from wind tunnel studies conducted at SpraySearch (Werribee, Australia) and New Mexico State University (Las Cruces, NM, USA) as described in [1]. Typically, three replicates were measured for each nozzle configuration and averaged for use in model simulations. In a few cases, where wind tunnel data were not available for a specific formulation, a substitute test substance (assumed to behave similarly to the field-trial tank mix) was used as a surrogate. The wind tunnel drop size distributions were each collected into 32 size classes. Model deposition as a function of distance is much smoother when none of the drop size classes contains more than 2% of the cumulative spray volume. Therefore, wind tunnel atomization data were linearly interpolated on a volume basis into additional size classes so that no size class held more than 2%.

Information on sprayed material required by the model includes the volumetric application rate, specific gravity, nonvolatile application rate, active ingredient application, and the evaporation rate of the tank mix. Volumetric application rates were calculated from field-measured application rates. Specific gravity was estimated as 1.0 for all water-based test substances and 0.92 for oil-based carriers. Nonvolatile and active application rates were calculated from the tank mix recipes and measured volumetric rates. Evaporation rates were obtained from laboratory data [22], with further correction of the data for low relative speed between the droplet and the local air stream [23].

Meteorological and environmental characteristics required for AgDRIFT include wind speed, wind direction, temperature, relative humidity, and surface roughness. The meteorological data were obtained at the SDTF field-study sites with instrumented 10-m meteorological towers [1]. Data were captured at intervals of 1 s for wind speed and wind direction and 10 s for temperature and relative humidity. Field logs time-stamped the beginning of each trial. Meteorological data were extracted for 10 min from that time to recover representative average data. Wind speed and wind direction were averaged following the unit vector approach [24]; temperature and relative humidity were obtained as simple averages of the raw data.

AgDRIFT assumes neutral stability for the air layer in which the spray material is dispersing and depositing. Therefore, the model determines the wind speed profile from the best estimate of the wind speed near release height above the ground (typically taken as 2 m) and a representative aerodynamic surface roughness. The wind speed and direction were sampled in the field at four tower heights (0.33, 1.83, 3.05, and 9.15 m). The 2-m average wind speeds were estimated from a least-squares curve fit of the average wind speed at the four levels. The aerodynamic surface roughness was inferred from extrapolation of the measured wind profiles that occurred during near-neutral atmospheric conditions. An average surface roughness was computed for each of the three sets of field tests. Wind direction is taken as that near the release height, i.e., 1.83 m. AgDRIFT uses an evaporation module that requires the wet bulb temperature depression as input. That single number (collapsing temperature and relative humidity effects) is calculated with an algorithm based on the Carrier equation [25], with the assumption that the ambient pressure was one standard atmosphere in each trial.

The spraying height of the aircraft was obtained by locating the center of the wheels (or the helicopter skids) from videotapes taken during the SDTF field trials. These heights were analyzed and summarized for use as model input by Stewart Agricultural Research (Macon, MO, USA). For the fixed-wing aircraft, ground measurements were made of the vertical distance from the center of the wheels to the tip of the trailing edge of the wing; for the helicopter, the assumption was made that the spray boom rested on the skids. The swath widths of the three test aircraft were all assumed to be 13.72 m (45 ft), the distance between flight lanes. In all spray trials, the edge of the field was set as one-half swath width downwind of the farthest downwind flight line.

For the comparison between AgDRIFT and field measurements of spray deposition and buffer zones in this study, the model input datasets were generated independently of the field deposition results. Neither the model algorithms nor the model input values were altered in an effort to obtain improved comparisons with the field data. In the jargon of model evaluation, this is considered a hands-off, independent evaluation.

Calculations and analysis

Both field and modeled deposition were normalized to the ideal (zero drift) in-field application rate and reported as a fraction of this rate. The application rate was calculated using the measured average flight speed and flow rate, lane separation of 13.7 m as the swath width, and a tank mix concentration based on the field mixing recipe. Although tank mix sampling and analysis was done for each application, doubts as to the accuracy of this measurement [1] led to the use of the concentration based on the mixing recipe rather than on the tank mix analysis.

One of the issues we face when comparing model predictions to observations is the presence of model input errors. If we can assume that these input errors are random, that the set of incorrect model inputs at least represents a population of values similar to the population of correct model inputs, and that the inputs are somewhat independent, then the errors become less important if we examine the differences in the distributions of predicted and observed deposition values. Venkatram [26] demonstrates the usefulness of comparing distributions. An informative method for comparing distributions is the empirical quantile-quantile (Q-Q) plot [27]. A Q-Q plot is a pairing of the predicted concentrations ranked highest to lowest against the observed concentration ranked in the same way. If the two distributions are identical, all the points would lie exactly along the $y = x$ (or 1:1) line. Departures from the line give us information about how the distributions differ. The Q-Q plots provide no information about the temporally paired relationships of predictions to observations.

Deposition in the SDTF trials varied approximately five orders of magnitude. Model performance is of interest over this entire range. The over- or underprediction ratio is a more important measure of model performance than is the absolute difference between predictions and measurements. A log transformation of the model predicted/observed ratio is centered on zero, is symmetrical for the same relative factors of over- or underprediction, and is approximately normally distributed. The transformed quantity e is defined as

$$e = \log_{10}(E) = \log_{10}(D_A/D_F) = \log_{10}(D_A) - \log_{10}(D_F)$$

where E is the model predicted/observed ratio, D_A is the deposition predicted by AgDRIFT, and D_F is the deposition measured in the field. If the model and data are in agreement $E = 1$ and $e = 0$. While both the mean ($\bar{e}$) and variance (σ_e) of e are of direct interest in this analysis, the quantities $E_a \equiv 10^{\bar{e}}$ and $\rho \equiv 10^{\sigma a}$ are also computed. E_a is a measure of the average over/underprediction ratio. ρ is a multiplicative factor, and when e ranges through $\bar{e} \pm \sigma_e$, E will vary from $\rho^{-1}E_a$ to ρE_a and provide an estimate of the expected range of over/underprediction ratios. Another measure of model performance recommended for the evaluation of regulatory models [19] is the fraction of cases that a model predicts within a specific factor (either over or under) of the field observation. The fraction that predicts within a factor of two ($f_{2\times}$), i.e. E ranging from 0.5 to 2.0, is calculated in this analysis. From a regulatory safety perspective, the fraction of the time the observed is less than the model prediction multiplied by a safety factor is a more pertinent statistic of interest and a factor, f_{2t}, indicating the fraction of the time the value of $E > 0.5$ was also calculated, which indicates how protective the model results are likely to be incorporating a safety factor of two.

Although downwind deposition is the primary AgDRIFT model output, the model results are used in a number of ways

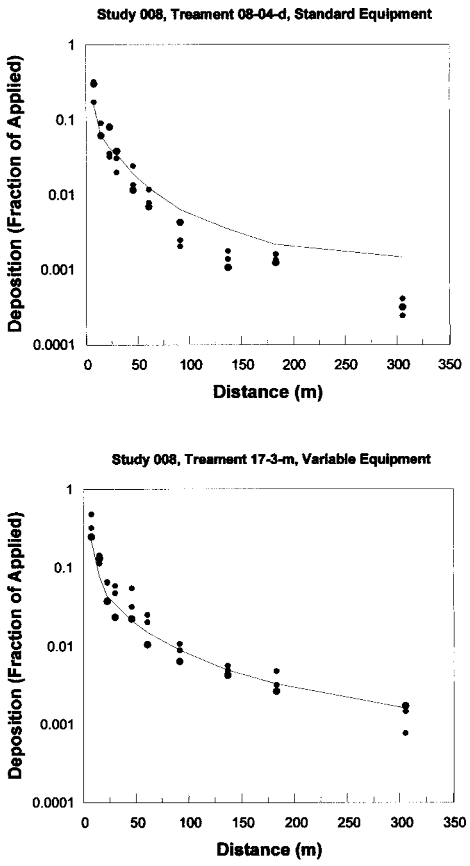

Fig. 1. Comparison of AgDrift® results (——) and individual card line data for a standard and variable equipment case field test (●).

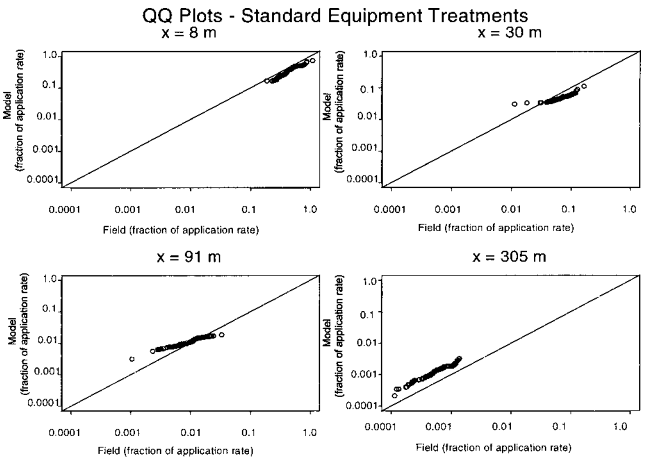

Fig. 2. Quantile-quantile (Q-Q) plots at four downwind distances plotting modeled deposition as a function of measured deposition (○) for standard case treatments. The straight line indicates perfect agreement in the distribution of modeled and measured values.

for estimating exposures to sensitive aquatic and terrestrial habitats. Defining buffer zones around these sensitive habitats within which the deposition amounts are equal to or below acceptable levels is one important end-use of the model. In particular, it is important to know if the model's response to management variables (e.g., drop size distribution, wind speed) is similar to that found in the SDTF studies and to what extent, if any, the model possesses bias in estimating buffer zones.

In the context of this analysis, a buffer or no-spray zone is defined as that distance from the downwind edge of the sprayed field beyond which the deposition rate drops below a specified level of concern. Four target levels were chosen for which to calculate buffer zones and compare the model estimates to the observations. These values as fractions of the application rate were 0.1, 0.05, 0.01, and 0.005. Downwind deposition values from either field measurements or model output were used to estimate (by simple linear interpolation between measurement location or, in a few cases, short linear extrapolations) the distance to the selected fractional rate. For each pair (modeled and observed) of buffer zones, a model/observed ratio was calculated and log transformed for analysis and graphical presentation analogous to the analysis for the deposition results.

RESULTS

Example plots comparing model and field deposition for two individual trials, a standard and a variable equipment case, are illustrated in Figure 1. Both the field data and model predictions are normalized to the application rate and plotted as a function of downwind distance. In these and subsequent analyses, downwind distance is reported as the distance perpendicular to the flight line, but model calculations are corrected to account for the increased transport distance due to the wind angle deviation from perpendicular. These two examples illustrate the variability of the line replicates for the field data and the range of deposition values observed as a function of distance. Deposition is plotted on a logarithmic scale since the values can decrease by two to four orders of magnitude or more from the edge of the field to the downwind measurement station, making differences between model and data results difficult to distinguish on a linear scale. In many cases, as illustrated in Figure 1 for the variable equipment case, model simulations are within the range of the line-to-line variability at all downwind distances. In other cases, simulation results differ substantially from the field results beyond 100 m, as illustrated in the standard equipment example plot in Figure 1.

The paired treatment design of the SDTF field trials results in two distinct datasets. In the standard equipment (or diazinon) treatments, both equipment (i.e., aircraft, boom and nozzle characteristics, release height, and speed) and tank mix formulation were held constant. This data subset is well suited for analysis of the response of drift to meteorological factors, including wind speed and direction, temperature, and relative humidity. In contrast, the much broader design conditions used in the variable treatments (malathion, carbaryl, or acephate tracers) permits this data subset to be used to analyze the impact of equipment and formulation variables on drift.

Figures 2 and 3 show the Q-Q plots for the standard and variable cases, respectively. The data have been further segregated according to the downwind distance at which the predictions and measurements were made. For both the standard and variable treatments, the modeled distributions of deposition close to the field of application (8 and 30 m) are similar to the observed distributions, as indicated by the closeness of the Q-Q slope to the 1:1 line. With these similar slopes, the range of observations matches the range of predictions. Since these are log-log (base 10) comparisons with a slope similar to the 1:1 line, any constant arithmetic offset (call it c) from that line represents a constant multiplicative (10^c) relationship between the predictions and observations. At 8 and 30 m for the standard treatments, the model is generally predicting at about 0.8 of the observations over the full range of deposition

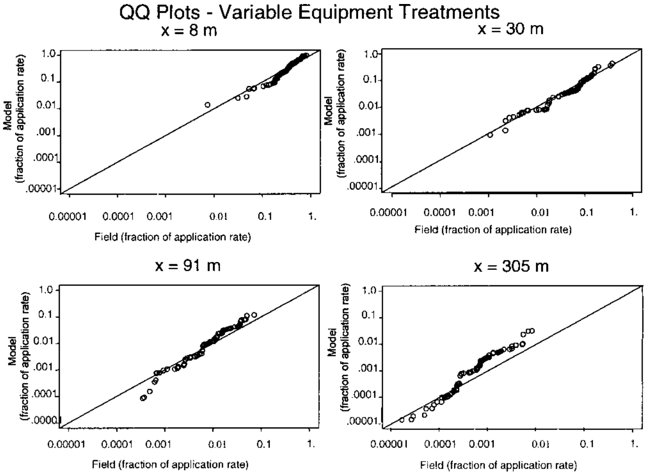

Fig. 3. Quantile-quantile (Q-Q) plots at four downwind distances plotting modeled deposition as a function of measured deposition (○) for variable case treatments. The straight line indicates perfect agreement in the distribution of modeled and measured values.

values. At these same distances for the variable treatments, the highest depositions are only slightly overpredicted, with the distributions generally matching well. At the most distant sampling location (305 m) for all the standard cases and the upper half of the variable treatments, the model is consistently overpredicting the observations by about a factor of two. However, for the lower portion of the variable treatments, the model is underpredicting deposition. These cases represent the large droplet helicopter cases and will be discussed in more detail subsequently.

Summary statistics for the standard and variable treatments as a function of distance are presented in Tables 2 and 3. The summary statistics (as with the Q-Q plots) indicate that the model underpredicts the standard treatment results in the near-field ($\bar{e}$ is negative and $E_a < 1.0$) while overpredicting results in the far-field ($\bar{e}$ is positive and $E_a > 1.0$). In contrast, the model appears to perform better on average with the variable treatment dataset and not to have significant under- or overprediction problems based on the mean values ($\bar{e}$ and E_a). However, the measures of variance (σ_e and ρ) are much greater for the variable than for the standard cases. Based on the $f_{2\times}$ values, the model predicts within a factor of two of the field data more often (at most distances) for the standard than the variable treatments. The single-tailed analysis represented by f_{2t} in Tables 2 and 3 indicates that the model predictions multiplied by a safety factor of two will generally be in excess of the observed value over 80% of the time. The only exception

Table 2. Summary statistics for standard equipment treatments

x (m)	$\bar{e}$	σ_e	E_a	ρ	$f_{2\times}$	f_{2t}
8	−0.11	0.14	0.78	1.37	0.90	0.90
15	−0.20	0.19	0.63	1.53	0.68	0.69
23	−0.21	0.14	0.61	1.37	0.76	0.77
30	−0.14	0.17	0.72	1.49	0.82	0.85
46	−0.10	0.20	0.79	1.58	0.83	0.86
61	−0.06	0.18	0.86	1.53	0.89	0.91
91	0.08	0.23	1.20	1.69	0.82	0.95
137	0.18	0.28	1.50	1.89	0.73	0.99
183	0.26	0.33	1.81	2.16	0.63	0.99
305	0.35	0.35	2.25	2.24	0.35	0.95

Table 3. Summary statistics for variable equipment treatments

x (m)	$\bar{e}$	σ_e	E_a	ρ	$f_{2\times}$	f_{2t}
8	−0.02	0.22	0.95	1.66	0.83	0.87
15	−0.03	0.28	0.93	1.89	0.74	0.86
23	−0.03	0.25	0.94	1.76	0.81	0.89
30	0.01	0.25	1.02	1.78	0.76	0.90
46	−0.06	0.29	0.87	1.97	0.73	0.81
61	−0.05	0.34	0.88	2.18	0.71	0.83
91	−0.01	0.49	0.97	3.12	0.67	0.87
137	−0.02	0.64	0.95	4.36	0.47	0.91
183	0.02	0.64	1.05	4.36	0.48	0.91
305	0.10	0.73	1.27	5.34	0.37	0.85

was in the near-field (15 and 23 m) for the repeated standard case studies.

A subset of trials where the variable equipment treatments had application parameters similar to the standard equipment treatments was analyzed to examine whether the difference between the model performance for the standard equipment and variable equipment treatments was due to the difference in tracers used in the two sets of data or to the range of application variables. This subset contains all the variable treatments that used the D6-46 nozzle with a 45° release angle on the standard, medium speed, fixed-wing airplane (18 treatments) at a low release height. The variable equipment treatments and the corresponding standard equipment treatments in this subset have nearly identical application and environmental conditions, differing only in the tracer used. Box plots as a function of downwind distance are shown in Figure 4 for both of these standard and variable equipment data subsets. Similar trends of slight underprediction at short range followed by overprediction far downwind are seen in both datasets. The data were compared using a *t* test on the ratio at each downwind distance. Statistically significant differences ($p \geq 0.05$) in means only occur at $x = 23$ m, and the difference in the means (0.086) is of no practical importance. Thus, it appears that the datasets are consistent with regard to the behavior of the tracers and that the broader range of conditions in the variable treatment accounts for differences in the model/data comparison occurring in the limited standard case dataset.

The standard equipment treatments are used to examine the

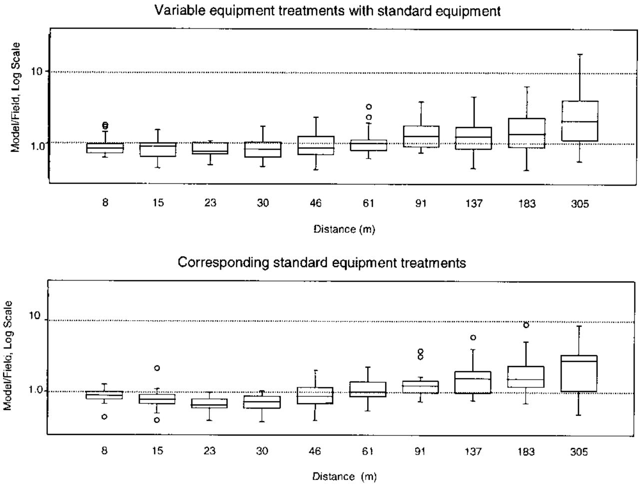

Fig. 4. Box plots of the ratio of model and field deposition as a function of downwind distance for variable treatments applied with standard-like conditions (top) and the corresponding standard case treatments (bottom).

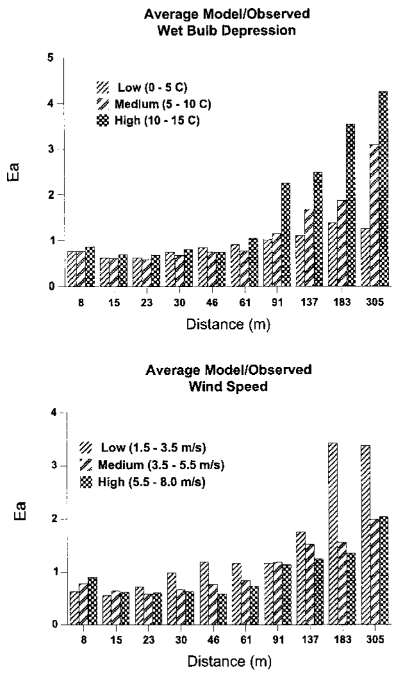

Fig. 5. The geometric average (E_a) of the ratio of model and observed results for standard case trials for wind speed and wet bulb depression categories as a function of downwind distance.

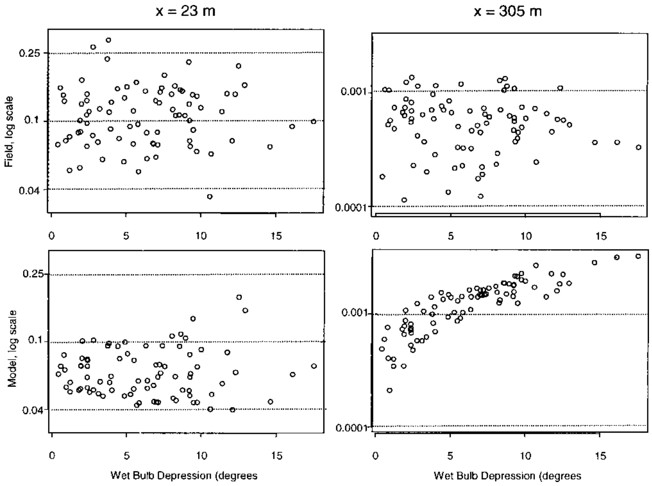

Fig. 6. The measured in-the-field and modeled deposition (fraction of the application rate) at 23 and 305 m downwind as a function of wet bulb depression.

sensitivity of the model/field ratio to the environmental factors. Meteorological data collected in the field included wind speed, temperature, and relative humidity. Wet bulb temperature is a function of both temperature and relative humidity and serves as a measure of the evaporative potential of the atmosphere. The response of model predicted/observed ratio (E_a) as a function of downwind distance and categories of wind speed and wet bulb temperature depression are shown in Figure 5. While for all categories the model/field ratio increases as a function of downwind distance, there is a substantial difference between low and high wet bulb conditions in the far-field. In the far-field, the model/observed ratio is very close to one at low wet bulb depression values, while during highly evaporative conditions, this ratio is greater than four. The effect of wet bulb depression is further illustrated in Figure 6, where the measured and modeled deposition levels are plotted as a function of wet bulb depression for two downwind distances. At the near-field location ($x = 23$ m), as expected, neither the field measurements nor the model predictions are correlated with wet bulb depression. At the far-field location ($x = 305$ m), however, the modeled deposition is well correlated with wet bulb depression whereas the field deposition is not.

The absence of correlation between far-field deposition and wet bulb depression (as measured in the field study) was unexpected. In high evaporative conditions, released droplets evaporate rapidly, decrease in volume (size), and have a greater drift potential. From this perspective, an increase in the percentage of far-field deposition might be expected, and the model results show this effect. However, these very small droplets may in fact simply remain airborne and not deposit on the collectors. However, the far-field data are nearer the detection level and there is high analytical variability, which makes detection of trends more difficult. In addition, wind deviations from the sampling media potentially lower sample collection at the far-field locations. The overall tendency of the model to overpredict deposition at the far-field sampling location illustrated in Tables 2 and 3 is explained to some extent by the discrepancy between the response of the model and field-trial results to wet bulb depression. The model does not account for local humidity increases generated by the spray and spray cloud, which could decrease evaporation rates. These differences are most likely due to a combination of the limitations in both the model and the dataset.

We next turn to the variable equipment dataset and examine the influence of controllable application factors (such as release height and droplet size) on the ratio of model prediction to field observations. The model/field ratios that deviate the farthest from one occur in the helicopter applications. This is shown in Figure 7, where the log of this ratio for the helicopter treatments is plotted as a function of downwind distance. Since there is a total of only 10 helicopter applications in the dataset, conclusions drawn based on this small dataset have a higher level of uncertainty than the much larger fixed-wing dataset. The treatments are further subdivided by nozzle type. The largest disagreement between model predictions and field measurements occurs when the D6-SS nozzle (a solid stream nozzle that generates a very coarse spray) is used on a helicopter. At far downwind distances, the model underpredicts by as much as two orders of magnitude, and the underprediction occurs at both low and high release heights. Since the helicopter treatments with finer sprays have model-predicted/observed values that are close to one and are in line with the balance of the variable equipment dataset, this difficulty appears to be associated with the very coarse spray rather than the helicopter algorithms. The question naturally arises as to whether this strong droplet size effect also occurs on fixed-wing aircraft. In Figure 8, the model to observed ratio is plotted as a function of downwind distance for the fixed-wing aircraft treatments, split into three different drop size categories based on the volume median diameter (the diameter at which 50% of the volume is contained in larger drops and 50% is contained in smaller drops). The middle graph contains all of the D6-46 nozzle treatments, the top graph contains the finer sprays, and the bottom graph shows the coarse, solid-stream nozzle treatments. Unlike the helicopter results, no dramatic shift in the ratio is observed with the coarse spray applications. However, there appears to be a small downward shift in the ratio (moving toward underprediction) as the droplet size increases that oc-

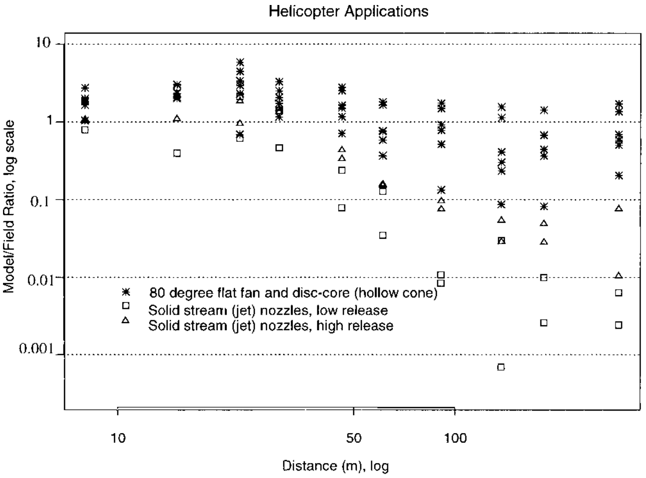

Fig. 7. The ratio of modeled and field deposition as a function of distance for helicopter applications identified by nozzle type and release height.

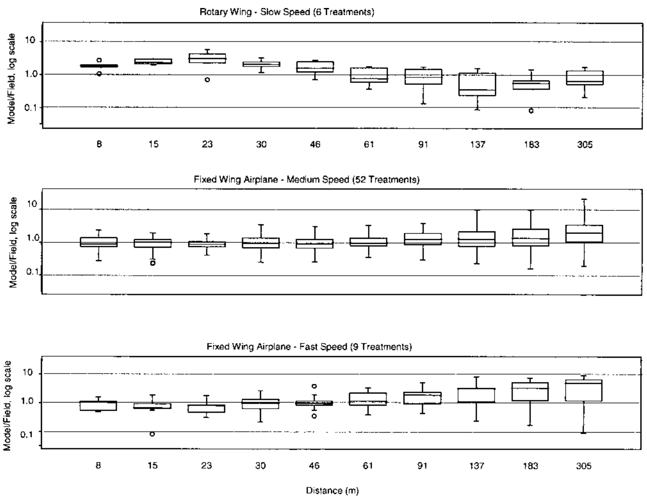

Fig. 9. Box plots of the ratio of model and field deposition as a function of downwind distance for three categories of flight speed.

curs at most downwind distances. For the faster fixed-wing application, the droplet size for the coarsest spray is significantly finer than for the helicopter application. The measured volume median diameter for the coarsest helicopter application is 811 μm but only 546 μm for the coarsest fixed-wing application.

The impact of aircraft type or, equivalently, flight speed is explored in Figure 9. Note that the helicopter graph contains only six treatments; box plots cannot accurately portray the distribution of the data when the dataset is this small. This graph should only be used to gain a sense of the location and spread of the data; the median and central quartiles have little meaning with so few data points. The over/underprediction trend in the helicopter treatments is reversed from the general fixed-wing trend, with overprediction at short distances and underprediction farther out. When compared with the medium-speed fixed-wing airplane, the trend in the fast fixed-wing airplane case is more exaggerated. Finally, in Figure 10, we look at the effect of release height on the residuals. Although we note an increase in residual variability coupled with a slight movement to greater overprediction at higher release heights, no remarkable features stand out.

A major use of the model is expected to be in calculating the width of buffer zones needed to limit deposition on sensitive areas to some percentage of the application rate. However, when the relative performance of the model is examined for calculating buffer zones for levels of deposition of concern, this is no longer as significant. In Figure 11, the model/observed ratio based on four target deposition rates (10, 5, 1, and 0.5% of the application rate) are shown as box plots. Generally, these results reflect the deposition results. The small target values show a slight overprediction of buffer zone size 0. The median results show less than a 20% bias. Although the tendency of the model to overpredict far-field deposition rates is the feature that draws the most attention in the previous analysis, this problem is relatively insignificant when predicting buffer zones protective to 0.5% of the application rate. Table 4 (standard equipment treatments) and Table 5 (variable equipment treatments) summarize statistics for the buffer zone analysis of residuals. For both the standard treatment and the variable treatment buffer zones for the four deposition levels, the model predicts a buffer zone within a factor of two 90% of the time.

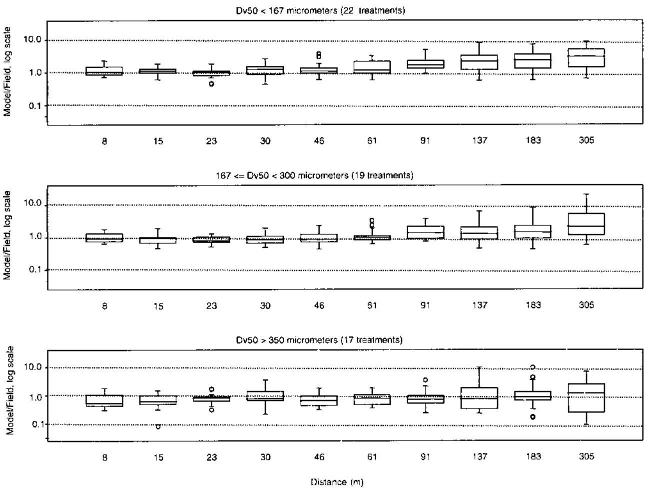

Fig. 8. Box plots of the ratio of model and field deposition as a function of downwind distance for fixed-wing aircraft (variable equipment treatments) for three drop size categories based on volume mean diameter D_{v50}.

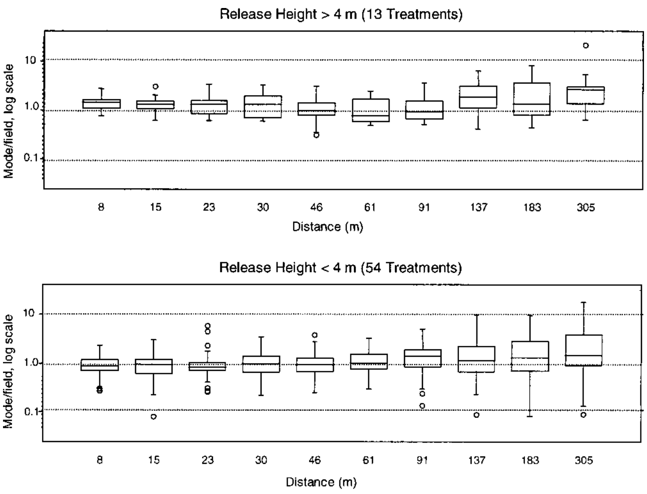

Fig. 10. Box plots of the ratio of model and field deposition as a function of downwind distance segmented by release height.

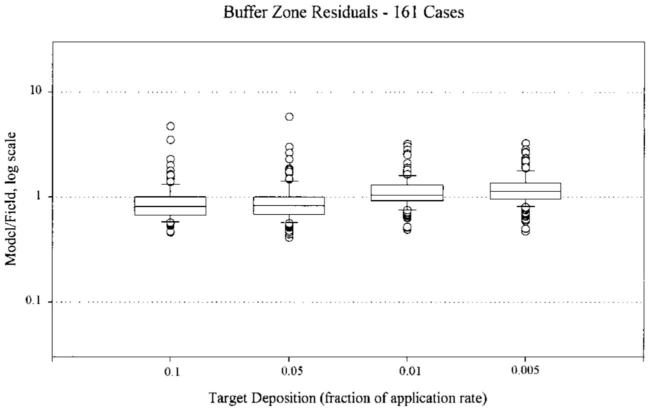

Fig. 11. Box plot of buffer zone residual for four deposition rates.

SUMMARY AND CONCLUSIONS

The SDTF field trials provided a rich database for use in model evaluation. The field data have a substantial amount of random variability that limits the ability to evaluate any model on a trial-by-trial basis. However, the number of trials used in the analysis (161) including the 82 standard case replicates of the same equipment allow us to make statements on the performance of the model in predicting average deposition. The deposition values from both the field trials and the model decreased by up to four orders of magnitude over the range of downwind distances considered in this study.

Overall, AgDRIFT predicts average field deposition levels reasonably well over the range of application conditions that are likely to be encountered in aerial agricultural applications. The model has a slight tendency to underpredict mean deposition levels in the near-field and to overpredict deposition at far-field distances. Buffer zones show similar over/underprediction trends to the deposition patterns but with lower magnitudes—bias is generally less than 20%. Over 90% of the distances to a target deposition rate (buffer zone size) computed from modeled deposition were within a factor of two of the value calculated from field observations for the four target deposition rates.

While both the observed and modeled deposition responded to wind speed in a similar fashion, this was not the case for wet bulb depression (a function of relative humidity and temperature, which is a measure of evaporative potential). AgDRIFT is sensitive to evaporative effects, and modeled deposition in the far-field responds to wet bulb depression, whereas the field observations do not. The differential response to relative humidity is sufficient to account for most of the overpredictive tendency of the model relative to the field trials in the far-field. The absence in the field observations of an evaporation effect on deposition is puzzling. The very small particles generated under evaporative conditions may have low collection efficiencies under turbulent conditions, which may mask the increase in drift with increasing evaporation. In addition, the low rate deposition field control spikes did not bound the deposition values observed at the far-field collectors, and it is impossible to definitively conclude that there is no loss from the collectors at these low levels.

Table 4. Summary statistics for standard equipment buffer zone residuals

Target deposition (% of application)	$\bar{e}_b$	σ_{eb}	E_{ab}	$\bar{e}_b$	$f_{2.0b}$
10	0.0342	0.0815	1.08	1.21	1.0
5	−0.1371	0.1029	0.73	1.27	0.98
1	−0.1270	0.1168	0.75	1.31	0.95
0.5	0.0595	0.0959	1.15	1.24	0.96

Table 5. Summary statistics for variable equipment treatment buffer zone residuals

Target deposition (% of application)	$\bar{e}_b$	σ_{eb}	E_{ab}	$\bar{e}_b$	$f_{2.0b}$
10	−0.0071	0.163	0.98	1.45	0.93
5	0.0041	0.1868	1.01	1.54	0.91
1	0.0412	0.1753	1.10	1.50	0.91
0.5	0.0627	0.1797	1.15	1.51	0.90

The number of helicopter applications during the trials was small and all were done with a single type helicopter. AgDRIFT strongly underpredicted deposition for four helicopter applications from coarse straight stream nozzles. The results from six other helicopter applications with two other types of nozzles that produced finer sprays did not display this underpredictive behavior. The fact that the results from applications with the other two nozzles were quite good suggests that either the helicopter algorithms do not handle very coarse droplets well or the measurements of the droplet spectra for the coarse nozzle is problematic. One problem may be in the extrapolation of laboratory (wind tunnel) measured droplet spectra for the simulation of field conditions. Very large droplets are sensitive to changes in shear forces and will tend to fragment with relatively little increase in shear. The wind tunnel configuration used to simulate atomization experiments considered only the forward speed of the aircraft and did not simulate any of the rotary-induced downwash, which changes the effective nozzle angle. Obtaining an adequate simulation of field-generated droplet spectra from very coarse spray nozzles may be a limitation for accurate use of the model. Additional model evaluation for helicopter applications needs to be pursued since the number of helicopter trials in the SDTF was very small and use of helicopters has potential for drift reduction relative to fixed-wing aircraft [28] since the flight speeds and therefore air shear are generally lower, facilitating the production of sprays with fewer relatively small droplets.

In general, the model shows a response similar to that of the field observations for the application variables, including droplet size and application height as well as wind speed. AgDRIFT was also in good agreement with field results for estimating buffer zones. Generally, this model appears satisfactory for regulatory evaluations, although care should be exercised when applying the model beyond the ranges tested here. Major limitations of the current algorithms are the assumptions of flat terrain and near-neutral atmospheric stability. Extension of the algorithms to handle stable atmospheric conditions along with the capability to estimate effectiveness of vegetative buffers and use in simulation of ground sprayer applications are model development efforts required to increase flexibility of AgDRIFT for use in spray drift exposure assessments.

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